Accurate and automatic surveying of beacon positions for a laser guided vehicle

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Abstract

In this paper we outline a system for automatic surveying of beacon positions for an autonomous guided vehicle. The vehicle measures the bearing to retro-reflective beacons using a laser scanner. As the vehicle moves, asynchronous measurements to unidentified beacons are obtained. The goal of the system is to automatically group those measurements that belong to the same beacons, to find all the erroneous measurements and to estimate the two-dimensional map of the beacon positions. Grouping of the beacons is achieved in a RANSAC type of algorithm. The map of the beacons is estimated using maximum likelihood estimation using bearing measurements and odometry. Recursive approximations of the estimation problem is used for increased speed.

Key words:

Autonomous vehicles, computer vision, laser sensor, automatic surveying.

1 Introduction

Autonomous guided vehicles are important in factory automation. One way, and the way that has been used traditionally, to guide the vehicle is by wires in the ground. This works, but is very inflexible. To change the path of the vehicle you have to rewire the wires. Another way that is much more flexible is to use a vehicle that, from the information where it is, can calculate where it is supposed to move next. An example of such a vehicle is a laser guided vehicle, see [1, 4, 6]. This vehicle is equipped with a laser that rotates and scans a horizontal plane of the premises. The surroundings are equipped with beacons in the form of reflective tapes. These give rise to reflections when hit by the laser. The bearing to the beacon relative to the heading of the vehicle is measured by a sensor that is mounted on the laser.

Introduce an object coordinate system which will be held fixed. The angle α defined above, depends on the position of the beacon (U_x, U_y) and of the position (P_x, P_y) and orientation P_θ of the scanner, cf.

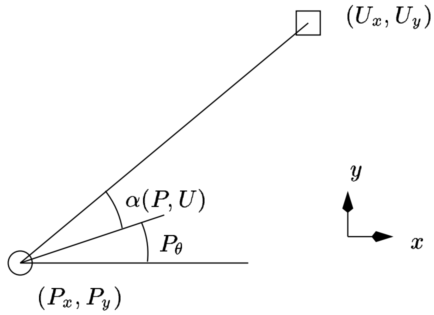

Figure 1: The figure illustrates the measured angle α as a function of scanner position (P_x, P_y), scanner orientation P_θ and beacon position (U_x, U_y).

Figure 1, according to

$$\alpha(P, U) = \operatorname{atan2}(U_y - P_y, U_x - P_x) - P_\theta \ , \qquad (1)$$

where atan2 is the four quadrant inverse tangent as explained in [5]. The vector (P_x, P_y, P_θ) is called the **meter state**. The actual measurement $\bar{\alpha}$ deviates from the true angle, due to noise and quantisation effects in the laser scanner:

$$\bar{\alpha} = \alpha(P, U) + \Delta\alpha \ . \qquad (2)$$

The position and the heading of the vehicle is calculated using these bearing measurements and the positions of the beacons, [6]. As the positions of the beacons have to be known, you have to develop a method by which you can calculate the map of beacons the first time that a new locale is encountered. Previously this was done in a semi-automatic way, see [2, 3]. The association of bearings was done manually, and then optimized by a computer. To do the association manually is not completely satisfactory, since it is both time-consuming and difficult, and therefore prone to errors. It would be much better to have a completely automatic procedure. This is the problem that is discussed in this paper. The time factor is not that important, since the map of beacons is only done one or a few times for a new area. The important thing is the precision of the map, that all beacon positions are accurate. Another important factor to be considered with a fully automatic procedure, is robustness.

The vehicle measures, apart from the bearings where reflections occur, the distance to the beacon and information about the vehicle's speed and the direction of the steering wheel. This information is used to calculate the odometry of the truck, i e the path that the truck has moved in.

The resolution of the scanner is about 1 mrad. Apart from random errors in the measurements of reflections there may be systematic errors due to misalignment of the laser and the mirror. Errors in the odometry may depend on loss of traction of the wheels of the truck, which causes the speed to be measured wrongly.

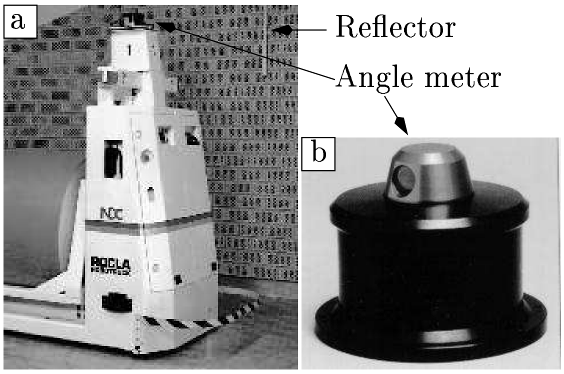

Figure 2: a: A laser guided vehicle. b: A laser scanner or angle meter.

2 General framework

As we have access to both odometry data and bearing measurements it would be desirable to use the combination of information in an optimal way. As the odometry data is most accurate on a smaller time scale the data log is divided into smaller segments. The path of the truck within the segment is then calculated using the odometry data. From this path and the reflections, the beacons are identified and incorporated into the map. The last step is an optimization, which is done over all the acquired data up to this point in time. The procedure is then repeated with the next segment from the data log.

3 Odometry

The vehicle used has three wheels, one front steering wheel, and two wheels on a back axis. It is assumed that the vehicle can only move in a direction normal to the back axis, i e the back wheels do not move side ways. The vehicle measures both its speed and its direction. The direction is registered as the angle of the steer wheel of the vehicle. From this information the path that the truck has moved in from an initial position can be calculated. This is simply done as adding small distances from the intitial position.

$$x = x_0 + \sum_i v_i \Delta t_i$$

This is how an origo on the vehicle has moved. The important information is how the position of the angle meter has moved. To calculate this position one has to know its position relative to the origo of the vehicle. Apart from this information the wheel base of the vehicle is known. The position of the angle meter is fixed on the vehicle, and hence the position of the angle meter moves in the same way as the origo. It not enough to know how the position of the angle meter has moved, it is also necessary to know how the angle meter has rotated in the coordinate system. This is done by calculating the angular velocity of the vehicle, Ω. From this the angle of the angle meter is calculated.

$$\theta = \theta_0 + \sum_i \Omega_i \Delta t_i$$

As the odoometry depends on several measured parameters, e g wheel base and position of angle meter, it would be nice to be able to optimize these parameters in the optimization procedure. To do this the derivatives of the position and angle of angle meter with respect to the different parameters are calculated. This is straight forward when one has the expressions for the position and angle of the angle meter.

4 Automatic association of measurements

Before the reflections are grouped the odometry for the current segment of data is calculated. The grouping of bearing measurements is done by the following method. First a bearing measurement is randomly chosen. From this angle one can predict projected angles for other times in the segment. If there are bearing measurements that correspond to this angle within some degree of accuracy these bearings are grouped. To check that these bearings correspond to an actual beacon two things have to be checked. First there has to be a minimum number of associated measurements, e g 4. Secondly the standard deviation of the difference between projected angles and measured angles must not be too large. If this is ok then a new reflector is created in the map. If it's not ok then the reflector position has to be established more accurately. This is done by choosing two bearings from the previously investigated. From these two measurements a new reconstruction is done. This is tried a few times or until a reflector position is established sufficiently correct.

The whole procedure is repeated until all the bearings in the segment have been associated or have been tried to be associated.

When a map of beacons has been established one can first of all, in a new segment, try to associate bearings with existing reflectors in the map. This is done by calculating the difference between the measured bearing and the projected bearing. The projected bearing is calculating using the odometry data and the earlier established map of beacons. Not all the beacons in the map are tried; only those that are active, i e the beacons that were used in the data segment prior to the current one.

5 Optimizing the beacon map

After a segment has been associated, the whole map of beacons is optimized and updated. The optimization is done over all the old segments and all the beacons in a nonlinear least-squares sense. All the relative positions of the truck in each segment are fixated so that only stiff body motion of an entire segment is allowed. Then the sum of the squares of the differences between the projected angles a_p and the measured angles a_m divided by the standard deviation σ in estimated angles, for all bearing measurements, is calculated,

$$f = \sum_i \left(\frac{a_p(i) - a_m(i)}{\sigma} \right)^2$$

This sum is minimized in a least-squares sense, with respect to the positions of the beacons in the map, the positions of the segments and some vehicle parameters. Every beacon gives rise to two variables, the x and y position, and every segment gives rise to three variables, x and y position of the midpoint of the segment, and the orientation of the segment. There are apart from these variables four vehicle parameters that describe the position of the angle meter on the vehicle. In total there a 4+n*2+m*3 variables, where n is the number of beacons and m is the number of measurement segments. The size of the residual vector is the same as the total number of bearing measurements that are associated. This grows with about 140 elements with every segment that is investigated. This means that the optimization becomes significantly slower the more segments that have been associated. In the trial runs that have been investigated, there have been about ten thousand bearing measurements in every run. This means that the vector that is to be minimized is quite large.

Let x denote linearized deviations of the unknown parameters (beacon map, vehicle motion etc) from the minimum. Let Y be the vector of weighted residuals $Y(i) = \frac{a_p(i)-a_m(i)}{\sigma}$. The derivative $A = \frac{\partial Y}{\partial x}$ gives valuable information about the quality of the estimate. The covariance matrix of the estimated parameters is $C[x] = (A^T A)^{-1}$ and the function f can be estimated as

$$f \approx f_0 + x^t (A^T A) x \tag{3}$$

close to the minima.

Let m be the number of measurements and n the number of estimated parameters. Using the cholesky factorisation it is possible to write $A^T A$ as $L^T L$, where L is an upper triangular matrix of size $n \times n$ as opposed to A which is of size $m \times n$. Since the number of measurements m is much larger than n, L is much smaller than A.

6 Recursive optimization of Beacon Map

As the number of segments increase, the number of measurements becomes very large. Each step of the optimization as described above takes longer and longer time. Since the estimate of the map does not change much after a while, it seems valid to use the approximation

$$f_{old} \approx f_0 + x^t (L^T L) x = f_0 + (Lx)^T (Lx) \tag{4}$$

instead of all the old measurements.

Optimizing the map using both new and old measurements

$$\min f = f_{old} + f_{new} = (Y_{old})^T (Y_{old}) + (Y_{new})^T (Y_{new})$$

is equivalent to minimising

$$= (Lx)^T (Lx) (+ (Y_{new})^T (Y_{new}) \ ,$$

i e minimising the square of

$$Z = \begin{bmatrix} Lx \\ Y_{new} \end{bmatrix} \ .$$

The derivative of Z with respect to the motion parameters is

$$A = \begin{bmatrix} L & 0 \\ \frac{\partial Y_{new}}{\partial x} & \frac{\partial Y_{new}}{\partial y} \end{bmatrix}$$

Motion parameters can be updated by solving

$$A \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} = - \begin{bmatrix} Lx \\ Y_{new} \end{bmatrix}$$

in a least-squares sense. The covariance matrix of estimated motion parameters x and y can now be estimated as

$$C[x, y]^{-1} = A^T A \ .$$

This method of updating the motion parameters is substantially faster since only the new residuals and their derivatives hava to be calculated in each step. The information in the old measurements is encoded in L.

7 Experimental Validation

The procedure seems to work adequately in most cases. Although it has only been tested on a small amount of data logs it seems that it finds all beacons

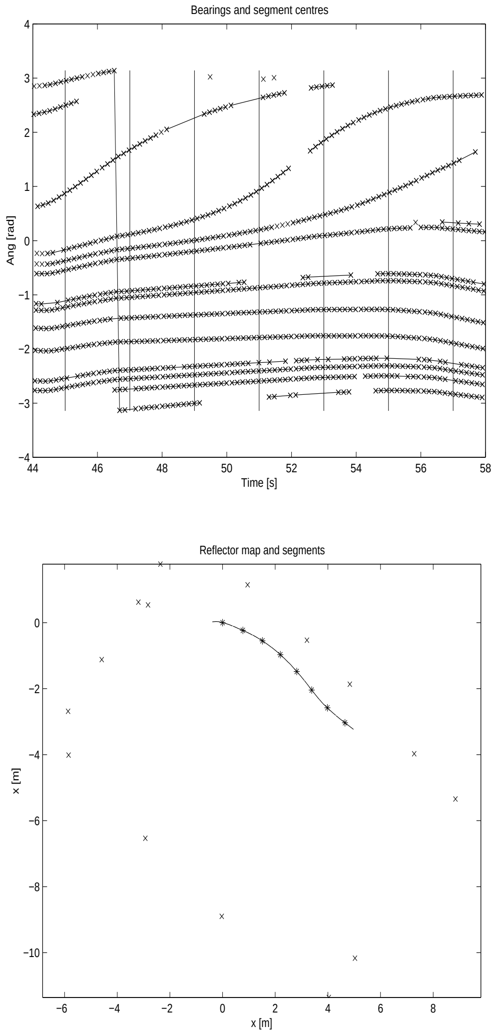

Figure 3: a: A log of bearings b: The reconstructed reflector map with the path of the truck.

and positions them correctly. The main functional problem seems to be that the algorithm finds more beacons than there are, that is, sometimes it does not distinguish between two beacons that in fact are one. The differences in the projected angles and the measured ones are in mrad which is about the accuracy of the angle meter. This implies that the algorithm does in fact calculate the map correctly.

8 Conclusions and Future Research

The procedure works almost automatically. At this stage the only thing that has to be done manually is to erase the double beacons. This should not be a problem in the future; Some form of reasoning has to be done to be able to erase false beacons and conclude that two beacons are indeed the same. This can maybe be done using the distance information in the data log.

The main practical problem is that it takes quite a long time to optimize the map after a while, since the optimization is done over all the segments that have been associated up to this point. This can be avoided by using the recursive optimization, which is much faster. It is still probably necessary to optimize the whole material every now and then.

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